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EEG Innovations in Neurological Disorder Diagnostics: A Five-Year Review

Madhuchhanda Basak [a*], Diptadip Maiti [b] and Debashis Das [b]

[a] *Computer Science & Engineering Department, Brainware University, Barasat, West Bengal, India.*
[b] *Computer Science & Engineering Department, Techno India University, Kolkata, West Bengal, India.*

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This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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Review Article

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ABSTRACT

The study provides a description of electroencephalography (EEG) advancements and their application in diagnosing and assessing various neurological diseases over the previous five years. The paper covers how EEG is used to examine epilepsy, sleep disorders, movement disorders, cognitive function, and brain damage. In epilepsy, EEG remains critical for seizure diagnosis, categorization, and localization of epileptogenic zones. Recent enhancements include the integration of machine learning techniques with high-density EEG equipment. In terms of sleep disorders, aberrant patterns suggestive of illnesses such as sleep apnea or narcolepsy may be diagnosed by a sleep architecture study utilizing EEGs, which can also be used to track therapy response. Cortical involvement occurs in Parkinson's disease and Huntington's disease, as well as other areas of the brain stem or basal ganglia. It helps researchers learn more about the cortical

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**Corresponding author: E-mail: madhuchhanda.basak@gmail.com;*

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damage produced by these disorders, which contributes greatly to understanding their pathophysiology. Aside from that, cognitive evaluation based on EEG has evolved via the creation of quantifiable biomarkers for early identification and monitoring of deterioration in Alzheimer's disease, among others. Traumatic injuries can damage brain functioning, hence knowledge regarding severity predicted outcomes can be acquired by Traumatic Brain Injury evaluation utilizing EEG.

Keywords: EEG; epilepsy; sleep disorder; movement disorder; brain injury assessment; cognitive assessment.

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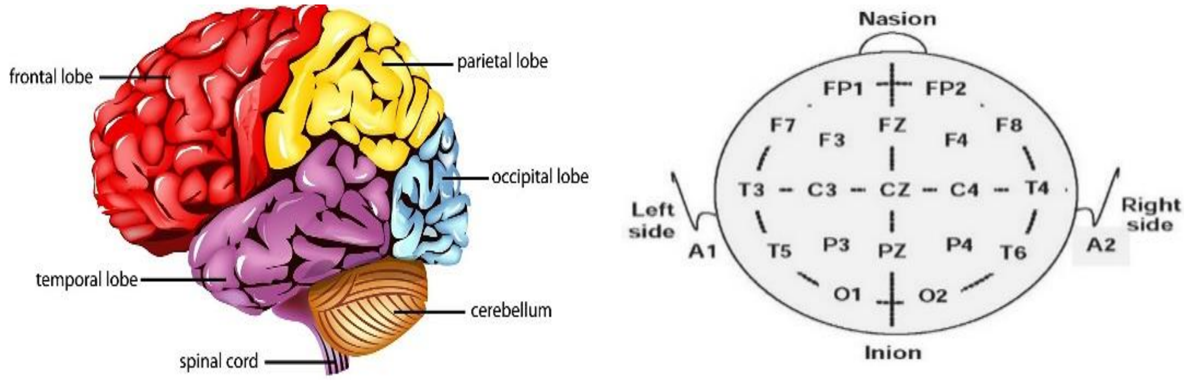
1. INTRODUCTION

Electroencephalography, or EEG [1], is a technique used to measure and record electrical activity in the brain. In order to identify and amplify the tiny electrical impulses that are generated by brain neurons, several electrodes are applied to the scalp. The brain experiences electrical activity due to neuronal communication, which uses electrical impulses to transmit information [2]. These electrical impulses may be detected by electrodes applied to the scalp; the resulting data is referred to as an EEG recording. Typically formed of conductive gel or paste, electrodes are tiny metal discs or sensors that are placed on the scalp [3,4]. The structure of human brain is presented in Fig. 1a and 10-20 electrode system is presented in Fig. 1b. The fundamental EEG acquisition procedure is depicted in Fig. 2.

The characteristics of EEG signals include their frequency, amplitude, and morphology, which can change based on neurological disorders, age, and brain state. When the brain is calm, awake, and the eyes are closed, alpha waves, which are oscillations in the 8–13 Hz range, are most noticeable. They are connected to a calm and relaxed condition and are usually seen across the posterior parts of the brain [5]. The higher frequency range of 14 to 30 Hz is occupied by beta waves, which are frequently seen during alertness, mental activity, and active attention. They typically cover the frontal and central areas of the brain, and during times of stress or worry, their amplitude may rise. Theta waves, which have a frequency range of 4 to 7 Hz, are frequently seen during light sleep, REM (rapid eye movement), and sleepiness [6]. They could also be present while in very relaxed or meditative states. Slow oscillations with a frequency range of 0.5 to 4 Hz, known as delta waves, are commonly seen in deep sleep phases like slow-wave sleep (SWS). Additionally, they are linked to neurological conditions and other brain illnesses such brain injuries. The high-frequency range of 30 to 100 Hz is attributed to gamma waves, which are linked to cognitive functions including perception, memory, and attention. They are believed to be involved in information processing and neural network synchronization since they are seen in task-related cortical activity [7]. Fig. 3 shows the different type of EEG Signals [8].

Epilepsy is frequently diagnosed and tracked by EEG. During seizures, it can identify aberrant electrical activity in the brain. Certain EEG patterns can be used to identify the kind of epilepsy and inform treatment choices [9]. In order to identify sleep disorders such narcolepsy, parasomnias, and sleep apnea, sleep medicine uses EEG. Identification of sleep phases and irregularities in brain activity while sleeping is aided by it [10]. Movement disorders including Parkinson's disease and Huntington's disease can be diagnosed and treated with EEG. Although EEG results in these diseases are frequently ambiguous, they can be augmented to the results of other diagnostic tests [11]. Assessing brain function after a stroke or Traumatic Brain Injury (TBI) might be aided by EEG. It can assist direct rehabilitation efforts by identifying irregularities in electrical activity that can suggest the degree of brain injury [12]. Although attention-deficit/hyperactivity disorder (ADHD) and autism spectrum disorder (ASD) are neurodevelopmental illnesses for which EEG is not usually the primary diagnostic technique, it can be utilized in research settings to look at underlying brain abnormalities [13].

In the last five years, EEG has become a vital diagnostic tool for a wide range of neurological disorders, providing information about both normal and abnormal brain activity [14]. Recent studies have demonstrated the effectiveness of EEG in precisely defining neurophysiological patterns linked to many illnesses, including epilepsy [15], movement abnormalities [16], and cognitive deficits [17]. This article summarizes the most recent developments in EEG-based diagnostics, illuminating how this field is developing in terms of comprehending and treating neurological disorders. The structure of the manuscript is as follows: Section 2 discusses the current trends in epilepsy diagnosis using EEG. The sleep disorder diagnosis related techniques are presented in Section 3. Advancements in movement disorder diagnosis using EEG are presented in Section 4. Approaches related to cognitive assessment is represented in the Section 5. Brain injury diagnosis procedures are conveyed in Section 6. A overall discussion on the various advancement in neurological diagnosis using EEG is expressed in Section 7. Section 8 and Section 9 holds the concluding remarks and future directives.



(a) Human Brain Structure **(b) 10-20 Electrode Placement Scheme**

Fig. 1. Human brain structure & 10-20 electrode placement scheme

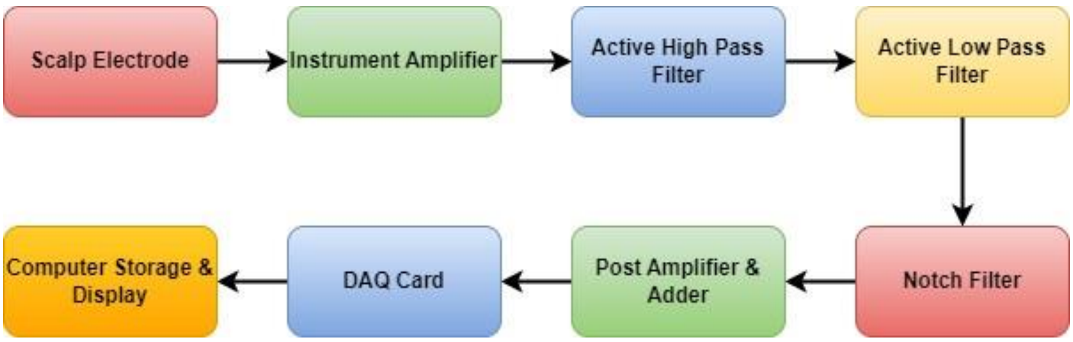


Fig. 2. EEG acquisition process

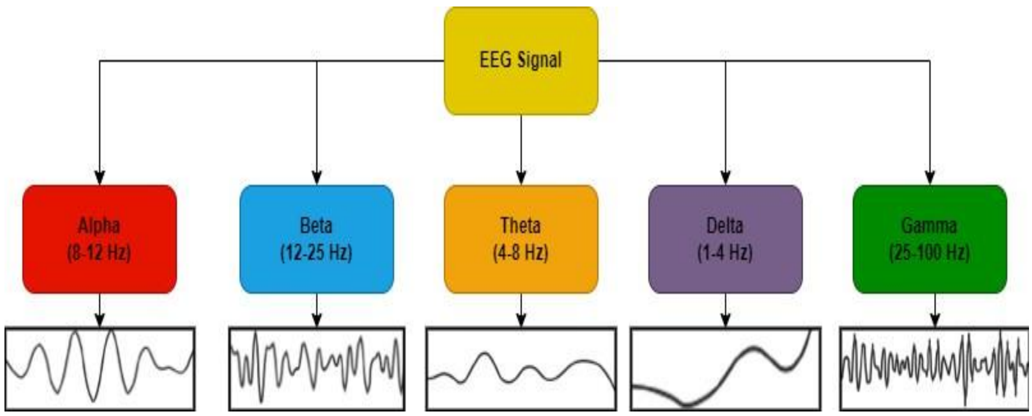


Fig. 3. Types of EEG signal

2. EPILEPSY DIAGNOSIS

Epilepsy is a neurological illness that is complicated and marked by recurring seizures. It is a major worldwide health concern. Abnormal electrical activity in the brain causes these seizures, which can cause a wide range of symptoms, from momentary consciousness lapses to convulsions. Even though epilepsy is common, it is nevertheless stigmatized and surrounded by myths, which negatively affects millions of people's quality of life globally. While antiepileptic medications continue to be the mainstay of epilepsy care, patients with drug-resistant epilepsy may find success with surgical procedures and neuromodulation methods. Even with these developments, managing epilepsy still presents some difficulties, such as getting a prompt diagnosis, having access to specialist treatment, and managing the psychological components of the illness. Improving results and people's quality of life requires a multidisciplinary approach including researchers, community support networks, and healthcare professionals.

An ensemble of pyramidal one-dimensional CNN models for EEG seizure detection is introduced by Ullah et al. [9], outperforming state-of-the-art techniques and attaining 99.1% accuracy on the University of Bonn dataset. Their method performs better on binary and ternary classification problems, with mean accuracies ranging from 97.4% to 100% when employing single and ensemble models.

According to Jaiswal et al. [18], SpPCA and SubXPCA combined with SVM are proposed for EEG seizure detection, and on benchmark datasets, they achieve 100% accuracy in differentiating between normal and epileptic signals. By using cross-subpattern correlation and subpattern-based PCA for feature extraction and classification, their approaches beat those of other researchers.

In order to improve efficiency and repeatability, Hao et al. [19] present DeepIED, a semi-automatic epileptic discharge detector for EEG-fMRI recordings based on deep learning. After testing 37 patients, the results showed a median sensitivity of 84.2% and a false positive rate of 5 events/min. This is much higher than the median sensitivity of 50.0% that was obtained using template-based approaches.

A deep learning framework for EEG-based epilepsy detection is presented by Abbasi et al. [14]. It uses LSTM architecture and achieves up to 98% accuracy for binary classification and up to 95% accuracy for multi-class classification of pre-ictal, inter-ictal, and ictal signals. They achieve great accuracies with their double-layered LSTM technique, outperforming SVM performance and proving useful in epilepsy detection by utilizing characteristics like Hurst Exponent and ARMA.

Following DWT preprocessing, Aliyu et al. [20] present an RNN for classifying epileptic EEG signals that achieves 99% accuracy with optimum settings. With 99% accuracy, their RNN beats LR, SVM, KNN, RF, and DT. DT comes in second with 98% accuracy, and RF has the lowest accuracy at 75%.

By detecting certain sub-bands (1.5-2 Hz and 11-12.5 Hz), Burenter et al. [21] provide a spectral analysis-based technique for epilepsy diagnosis using seizure-free EEG recordings, reaching 99% accuracy and outperforming neurologist benchmarks (70-95%). Research on healthcare information systems may benefit from this approach, which provides a reliable, quick, and affordable diagnostic substitute.

Using DWT and arithmetic coding, Amin et al. [22] provide a CAD approach that achieves 100% accuracy in separating epileptic seizure signals from normal EEG data. Perfect sensitivity and specificity are shown by the approach in several datasets, indicating that it may be a useful addition to clinical epilepsy diagnosis.

In order to detect epileptic seizures, Chatzichristos et al. [23] present a multi-view fusion model that uses attention-gated U-nets and LSTM. This model outperforms previous techniques on the TUH EEG seizure dataset and receives the highest TAES score in the Neureka 2020 Epilepsy Challenge. Even with a large number of false alarms every day, the sensitivity stays below 25%.

In order to train a multi-class classifier, Xu et al. [24] provide a self-supervised learning method for EEG anomaly detection using scaled transformations on regular EEG data. With an AUC of 0.943, the approach beats conventional anomaly detection techniques and shows resilience in cross-validation testing with respect to different classifier architectures and hyper-parameters.

Using artificial neural networks (ANN) and other classifiers, Mardini et al. [25] provide an EEG-based seizure detection framework that achieves a high accuracy of 97.82% in differentiating between epileptic and normal signals across 14 dataset combinations. Their approach offers a useful tool for identifying brain abnormalities and may find use in medical diagnostics and neuroscience research.

A thorough technique for detecting epileptic seizures including preprocessing, feature extraction, and classification. It is implemented in MATLAB and TensorFlow 2/scikit-learn by Malekzadeh et al. [26]. By utilizing 10-fold cross-validation, the technique attains 99.5% accuracy, indicating potential for improving the quality of life for those with epilepsy.

In order to diagnose epilepsy based on scalp EEGs, Thangavel et al. [27] present a deep learning method that uses 1D ConvNets. This method achieves a false detection rate of 0.23/min at 90% sensitivity. With mean EEG classification BAC of 78.1% (AUC 0.839) in LOIO cross-validation and 79.5% (AUC 0.856) in LOSO CV, the technique shows promising performance and may be useful in lowering the amount of human labour required for epilepsy diagnosis.

In order to achieve high accuracy (sensitivity: 98.09%, specificity: 98.69%, false detection rate: 0.24/h) in automated epileptic seizure detection from EEG signals, Zubair et al. [28] use dimensionality reduction strategies and machine learning models. Their approach outperforms earlier state-of-the-art studies and shows promise for improving seizure detection accuracy and efficiency, which will help people with epilepsy and medical professionals.

In their article Shankar et al. [15], describe a deep learning method that uses CNNs to identify epileptic seizures from EEG signals. This method produces RP-based 2D pictures for certain brain rhythms and achieves up to 93% accuracy on databases from Bonn University and CHB-MIT. The δ rhythm is shown to be the appropriate brain rhythm for seizure analysis, and global statistical metrics and entropy are used to assess the quality of RP images.

A CNN-LSTM hybrid model is presented by Jiwani et al. [29] for the identification of epileptic seizures from EEG recordings. It uses both spatial and temporal information and has fewer trainable parameters. The model's applicability for real-time processing applications is demonstrated by its up to 100% accuracy in differentiating between healthy persons and seizure sufferers when tested on the University of Bonn dataset.

Christou et al. [30] use the University of Bonn dataset to test the effects of different window sizes on the classification of EEG signals using BFGS, multistart, modified GA, and K-NN classifiers. According to the study, the multistart technique outperforms BFGS, modified GA, and K-NN, with a 20–21 second window obtaining the maximum accuracy (81.59%).

3. SLEEP DISORDERS DIAGNOSIS

The diagnosis of sleep problems is a complex task because of the wide range of symptoms and their influence on general health and well-being. From narcolepsy and parasomnias to insomnia and sleep apnea, sleep disorders cover a wide range of disruptions, each with its own clinical presentations and underlying causes. A thorough evaluation that includes a full medical history, a clinical assessment, and objective sleep investigations like actigraphy and polysomnography is frequently necessary for an accurate diagnosis. By evaluating nocturnal activities, respiratory data, and sleep architecture, these diagnostic techniques help determine the kind and severity of sleep disorders. Furthermore, new technologies and sleep monitoring gadgets for use at home present chances for remote monitoring and diagnosis, improving patient accessibility and convenience. To maximize diagnostic accuracy and treatment success, multidisciplinary teamwork and patient-centered care methods are crucial. Nevertheless, difficulties still exist in the prompt identification and management of sleep disorders.

Without the need of spectrograms or manually created features, Chambon et al. [10] offer a deep learning technique for temporal sleep stage categorization utilizing multivariate time series data.

The model leverages PSG inputs, such as EEG, EOG, and EMG, and uses linear spatial filters and softmax classifiers to achieve state-of-the-art performance in identifying sleep phases. It shows that recognizing W stage has a high specificity (almost 1) and sensitivity (0.85).

Using a time-distributed 1-D convolutional neural network trained on the Sleep-EDF dataset, Koushik et al. [31] present a real-time sleep staging system that uses deep learning on a smartphone with a wearable EEG, achieving 83.5% accuracy in five-class sleep stage categorization. The traditional gold standard for sleep staging, polysomnography (PSG), is simplified and automated using this method.

The Random Forest classifier outperformed other classifiers with an accuracy of 75.29% when used in Tzimourta et al. [32]'s approach for sleep staging utilizing EEG data from PSG recordings. In addition to possibly improving the identification of sleep problems, this method presents a viable path for a quick and affordable sleep examination.

Using obstructive sleep apnea (OSA) detection as a focal point, Korkalainen et al. [33] provide a deep learning approach for sleep stage division. With EEG+EOG, the model achieved 83.9% accuracy for sleep staging, with accuracy decreasing with OSA severity. This model was successful in both healthy persons and patients with suspected OSA.

A deep learning model called DOSED is introduced by Chambon et al. [34] to automate the detection of micro-architecture events in EEG data. When it comes to precise event location, duration, and type prediction—all of which are critical for identifying sleep disorders—DOSED exceeds existing state-of-the-art methods.

Using a decision tree-based multi-class support vector machine classifier, Ravan et al. [35] offer an EEG-based machine learning strategy that achieves 94.2% classification accuracy across three sleep categories for quantifying sleep quality. Even with untested datasets, the approach helps physicians diagnose sleep problems by providing a reliable and accurate assessment of sleep quality. In their study, Buettner et al. [36] provide a fast and precise machine learning technique for identifying sleep disorders, namely REM sleep behaviour disorder. They surpass previous standards, obtaining over 90% accuracy using a mere 10-minute EEG recording clip. The speed and precision of identifying sleep disorders—which is vital for preventing secondary illnesses like Parkinson's or dementia—can be greatly improved with this method.

Using deep learning on photoplethysmography (PPG) data, Korkalainen et al. [37] correctly estimate total sleep time and the apnea-hypopnea index (AHI) with accuracy rates of 80.1%, 68.5%, and 64.1% for three, four, and five-stage sleep classifications, respectively. This technique may make it easier and more affordable to diagnose sleep problems, particularly obstructive sleep apnea (OSA). In order to identify patient groups with sleep-related illnesses, Jarchi et al. [38] provide a bio-signal processing and deep learning approach that outperforms state-of-the-art classifiers and achieves 72% accuracy. By integrating ECG and EMG data, their suggested deep neural network design provides thorough analysis for the diagnosis of disorders including restless legs syndrome (RLS) and obstructive sleep apnea (OSA).

With high accuracies ranging from 91.3% to 99.2% using ensemble boosted trees classifier, Sharma et al. [39] propose an EEG-based method for automated identification of six sleep disorders, providing a quick and easy way to diagnose sleep disorders in homes and clinics.

A thirty-layer CNN model using EEG signals is introduced by Sudhakar et al. [40] for the detection of sleep disorders. AlexNet outperforms GoogleNet with an accuracy of 93.33%, showing promise even with a small dataset size.

An automated sleep stage classification system employing EEG signals and supervised classifiers is presented by Sharma et al. [41]; for balanced datasets, it achieves up to 92.8% accuracy and 0.915 Cohen's Kappa coefficient. For diagnostic reasons, the approach may be used in sleep labs and provides a dependable means of evaluating the quality of sleep in individuals suffering from different types of sleep disorders.

Using bidirectional recurrent neural networks for sleep EEG signals, Fu et al. [42] create a deep learning model that achieves 70–85% classification accuracy for each category on the Sleep-EDF dataset. Their approach outperforms previous models in terms of accuracy, indicating its efficacy and potential for real-world use in sleep study.

Using deep learning models trained on 135 EEG signals acquired with AES, Leino et al. [43] offer an accurate automated sleep staging approach based on ambulatory forehead EEG, attaining up to 89.1% accuracy. The model shows good ability to discriminate between different stages of sleep, especially when using the Fp1/Fp2 EEG channel combination.

4. MOVEMENT DISORDERS DIAGNOSIS

EEG-based movement disorder diagnosis is a developing field of study that aims to clarify the neurological underpinnings of motor dysfunction. EEG can offer important insights into cortical involvement and abnormal brain activity associated with illnesses including Parkinson's disease, Huntington's disease, and dystonia, even though it is not usually the primary diagnostic tool for movement disorders. Event-related potentials, aberrant oscillatory activity patterns, and cortical synchronization can all be seen in EEG recordings, which can provide further data for neuroimaging research and clinical evaluations. EEG can also help distinguish movement disorders from other neurological illnesses that share symptoms, which can lead to a more precise diagnosis and better treatment planning. Even though EEG has great potential, issues like low spatial resolution and variability in EEG results among people with movement disorders highlight the need for more research and integration of EEG with other diagnostic modalities for a thorough assessment and treatment of these intricate conditions.

The deep convolutional neural network technique presented by Vrbancic et al. [11] outperformed conventional approaches, however it lagged slightly below the state-of-the-art approach in terms of accuracy when it came to identifying motor impairment neurological diseases from EEG data. Nevertheless, it streamlines the diagnosis of neurological disorders by providing totally automated categorization devoid of human involvement.

Mumtaz et al. [44] developed an automated diagnosis system for Major Depressive Disorder based on EEG-derived synchronization likelihood (SL) features, with high accuracy rates of 98% for SVM, 91.7% for LR, and 93.6% for NB classification. Their findings suggest a viable new approach for diagnosing depression by demonstrating how EEG-based features may consistently identify MDD patients from healthy controls.

By employing an additional tree classifier, Vanegas et al. [45] achieve virtually flawless classification performance with an AUC of 0.99422 when proposing machine learning-based detection of EEG biomarkers in Parkinson's disease during visual stimulation. In addition to offering important insights into the neurophysiological hallmarks of the disease, their work emphasizes the potential of EEG spectral amplitude across various frequency bands for precise PD diagnosis.

To diagnose and prognosticate idiopathic Rapid Eye Movement Behaviour Disorder (RBD), Ruffini et al. [46] present deep learning models based on eyes-closed resting EEG data. Using both deep convolutional neural networks (DCNN) and deep recurrent neural networks (RNN), their method—which draws inspiration from audio or picture classification— achieves about 80% classification accuracy, demonstrating the promise of deep learning in EEG data for cognitive problem identification.

For the purpose of classifying motor imagery EEG signals, Dai et al. [47] present a unique deep learning framework that combines convolutional neural networks (CNN) with variational autoencoders (VAE). This approach outperforms current approaches, demonstrating a 3% improvement on the BCI Competition IV dataset 2b. With an average kappa value of 0.564, their method—which combines time, frequency, and channel information—achieves the greatest results and shows promise for motor imagery EEG categorization.

By using automated machine learning approaches, Koch et al. [48] are able to categorize EEG signals in patients with Parkinson's disease (PD) with an 84.0% classification accuracy using automated calculated features. Their method suggests novel biomarkers for Parkinson's disease (PD) cognitive function and demonstrates that a greater accuracy of 91.0% may be achieved by combining automated and clinical aspects.

Transfer learning of pre-trained Convolutional Neural Networks (CNNs) is used by Shajil et al. [49] to classify motor imagery (MI) EEG signals. The highest classification accuracy of 82.78±4.87% was achieved for the BCI Competition IV dataset 2a and 83.79±3.49% for an acquired dataset using InceptionV3 CNN. Their work demonstrates how well pre-trained CNN models—especially those with more layers and parameters—may be used to efficiently classify two-class MI EEG data.

Bouallegue et al. [50] propose a dynamic filtering and deep learning-based technique for detecting neurological illnesses based on EEG data. This method combines FIR and IIR filters with a Gated-Recurrent Unit (GRU) Recurrent Neural

Network (RNN) for preprocessing. Using Convolutional Neural Networks (CNN), their system achieves remarkable accuracy in feature extraction and classification, with 100% accuracy in diagnosing epilepsy and 99.5% in diagnosing autism.

The thirteen-layer CNN architecture proposed by Oh et al. [51] achieves 88.25% accuracy, 84.71% sensitivity, and 91.77% specificity in the identification of Parkinson's disease (PD) using EEG signals. This approach, which eliminates the requirement for traditional feature representation phases, shows promise as a dependable, long-term PD diagnosis tool when verified using stratified ten-fold cross-validation.

Using machine learning methods and the Maximum Overlap Discrete Wavelet Transform (MODWT), Abdulwahab et al. [52] create an EEG Motor-Imagery BCI System. Achieving 98.81% average accuracy using SVM algorithm using MODWT for feature extraction, their work highlights the importance of EEG for severe motor disorders, rehabilitation, and communication.

Using raw MRIs to identify microstructural neural network biomarkers, Bashir et al. [53] present DystoniaNet, a deep learning-based technique for aided diagnosis of movement disorders, especially isolated dystonia. With an overall accuracy of 98.8%, DystoniaNet outperforms shallow machine learning networks, demonstrating the promise of computational intelligence in the early identification of movement disorders.

Using resting state EEG data, Shaban et al. [16] provide a deep learning-based framework with 98% accuracy, 97% sensitivity, and 100% specificity for automated Parkinson's disease (PD) screening and classification. This framework supports doctors in diagnosis and treatment recommendations by acting as an accurate and dependable computer-aided diagnostic tool.

In comparison to traditional research, Urtnasan et al. [54] achieve a superior F1-score of 92% using deepPLM, a deep learning model for automated identification of periodic limb movement syndrome using ECG signals. With excellent accuracy in test, assessment, and training groups, it presents a viable substitute for PLMS screening, especially for home health care services.

A deep neural network technique for automatically determining movement intention from EEG data is presented by Shahini et al. [55]. High accuracy of 96.9% and 89.8%, respectively, are attained for two-class and three-class situations. This method outperforms prior approaches that rely on manual feature extraction since it operates directly on raw EEG data without feature extraction.

In order to diagnose Parkinson's illness, Shaban et al. [56] describe a deep learning technique that applies a 20-layer CNN to the Wavelet domain of resting-state EEG. With a high specificity and sensitivity of about 99.9%, the method is successful in correctly dividing people into two groups: those with Parkinson's disease (with and without treatment) and healthy controls.

5. COGNITIVE ASSESSMENT

EEG-based cognitive evaluation has become a useful technique for studying brain activity and evaluating cognitive functions. EEG, a non-invasive way of monitoring brain electrical activity in real time, provides insights into the neural dynamics associated with a variety of cognitive functions such as executive function, memory, and attention. Examining EEG data allows researchers to identify neural signatures that signal cognitive states, task involvement, and cognitive load. In addition, event-related potentials (ERPs) derived from EEG data give precise temporal resolution and may be used to investigate cognitive processes with millisecond accuracy. Moreover, quantitative EEG (qEEG) analysis offers quantifiable measurements of brain activity, making it possible to find biomarkers linked to neurodegenerative illnesses including Alzheimer's disease and cognitive decline. It is possible to diagnose cognitive deterioration early, track the course of a disease, measure the effectiveness of treatment, and improve patient care and cognitive rehabilitation techniques by incorporating EEG-based cognitive evaluation into clinical practice.

An end-to-end deep neural network model was created by Almogbel et al. [13] to directly predict cognitive effort from raw EEG data. For a 150-second window, the model achieved an astounding 95.31% accuracy. Their CNN-based method successfully recovers high-level characteristics from EEG data, showing promise for precise cognitive strain assessment with much room for improvement.

Using cutting-edge machine learning techniques, Liu et al. [57] provide an EEG-based evaluation of mental tiredness across four levels. Their work emphasizes the trade-off between recognition rates and practicality, stressing prospects for future accuracy increases in subject-independent techniques. They achieve an average accuracy of 93.45% in subject-dependent approaches and 39.80% in subject-independent approaches.

In human-machine collaboration situations, Yang et al. [58] provide a deep learning-based method for quantifying cognitive mental effort using EEG signals. By utilizing subject-specific integrated deep learning committees, their ensemble classifier surpasses standard classifiers in accuracy, achieving 92%, but at the cost of greater computing complexity and parameter overhead.

Using EEG spectrum data and traditional machine learning, Plechawska et al. [59] offer a subject-independent technique for cognitive workload estimation that achieves up to 91% accuracy using kNN model validation and cross-validation. Selecting features improves classification accuracy, proving useful in task level estimate.

A deep neural network is introduced by Almogbel et al. [60] to detect cognitive workload and driving context directly from raw EEG signals. The network achieves an average accuracy of 96% and can distinguish between driving on a city or highway with accuracy, indicating the effectiveness of deep CNNs in workload and context classification without the need for preprocessing.

In comparison to traditional techniques, Sridhar et al. [61] achieve enhanced diagnosis of mild cognitive impairment (MCI) by introducing a subject-agnostic BLSTM network to assess cognitive functions based on brain signal characteristics. The work shows potential fir accuracy in detecting MCI by using gamma band power analysis and sensory-motor paradigms to determine cognitive deterioration.

In order to distinguish between writing and typing activities, Qu et al. [62] suggest an EEG-based technique that uses machine learning and deep learning algorithms to achieve accuracy levels above chance. According to their research, EEG indicators are able to identify minute differences in cognitive tasks, even when the tasks' communication and cognitive modes are equivalent.

A methodology for separating moderate cognitive impairment (MCI) patients from healthy controls using EEG data is put forth by Siuly et al. [63]. By utilizing auto-regressive model features and Permutation Entropy in conjunction with contemporary machine learning techniques, they surpass previous approaches and offer a reliable biomarker for MCI identification, attaining a remarkable 98.78% accuracy rate through the use of Extreme Learning Machine.

In order to differentiate Parkinson's Disease patients based on cognitive function, Geraedts et al. [64] present a completely automated machine learning pipeline that uses EEG signals and achieves a mean accuracy of 92%. This method shows potential for cognitive profiling in PD patients undergoing Deep Brain Stimulation screening.

To identify cognitive burden, Gupta et al. [65] suggest a technique that combines deep learning with EEG-based functional connectivity, resulting in state-of-the-art accuracy of 80.87%. The study shows how functional connectivity information may be used for workload categorization in real time.

For the purpose of classifying EEG signals, Suchetha et al. [66] offer two unique deep learning architectures: SCN and MBCN. MBCN outperforms SCN and conventional approaches, reaching 88.33% accuracy and displaying reduced computing complexity.

An integrated EEG, eye tracking, and neuropsychological test low-cost screening paradigm for MCI is presented by Jiang et al. [17]. With predictive power of 84.5 ± 4.43% and 88.8 ± 3.59% in two cohorts, respectively, and AUCs of 0.941 and 0.966, the model has potential for use in the prediction of cognitive decline in the future.

Using EEG data and deep learning methods, Longo et al. [67] provide a self-supervised approach for modelling mental workload. Promising accuracy and generalizability are demonstrated by the approach, with a mean absolute percentage error of around 11% and consistent accuracy among individuals.

The effectiveness of a single-channel EEG device for assessing cognitive states is evaluated by Molcho et al. [68]. Their results point to a promising approach for identifying cognitive decline that may find widespread clinical application: machine learning-based EEG characteristics taken from an auditory cognitive exam.

6. BRAIN INJURY ASSESSMENT

EEG is a useful tool for brain injury assessment for assessing neurological function after traumatic brain injury (TBI) and other types of brain injury. With the sensitive and non-invasive monitoring of brain activity provided by EEG, doctors can identify anomalies in electrical transmission linked to brain damage. After an acute insult, EEG can give instantaneous information on the degree and kind of neuronal damage, which can assist influence treatment choices and forecast patient outcomes. Additionally, non-convulsive status epilepticus and subclinical seizures, which are frequent aftereffects of brain injury and may exacerbate secondary brain damage if ignored, can be identified by EEG monitoring in the critical care unit. Furthermore, quantitative EEG (qEEG) analysis may measure alterations in patterns of brain activity over time, offering significant prognostic data and directing activities related to rehabilitation. Even though EEG is useful, there are still issues that need to be addressed in order to maximize its application in brain injury evaluation and therapy. These issues include how to interpret EEG results in the context of multifactorial brain damage and the requirement for standardized procedures.

In order to detect epileptiform activity in rat EEG records following traumatic brain injury, Obukhov et al. [12] create a technique that uses wavelet transform and logistic regression, with an accuracy of around 80%.

Using EEG reactivity data, Amorim et al. [69] created a semi-automated technique that predicts outcomes in hypoxic-ischemic brain damage, with AUCs of 0.8 for random forest, which is equivalent to expert evaluation. Promising support for prognostication in cardiac arrest is provided by this approach.

In a mouse model of traumatic brain injury (TBI), Vishwanath et al. [70] classified EEG data using machine learning methods, namely CNNs, and achieved accuracies of up to 92.03% when evaluating sleep and wake data. Their results point to the possibility of using these methods to diagnose neurological disorders such traumatic brain injury.

A computer-aided method for automatically identifying Disorders of Consciousness (DoC) in brain-injured patients using EEG signals is presented by Wang et al. [71]. With a support vector machine classifier ensemble, their technique achieves a high accuracy of 98.21%, showing remarkable possibilities for precise diagnosis and medical treatment.

Deep neural network designs are proposed by Faghihpirayesh et al. [72] for the automated identification of biomarkers for post-traumatic epilepsy (PTE) in patients with moderate-to-severe traumatic brain injury (TBI) using EEG data. Their recurrent neural network provides a potential path for reliable, automated PTE detection and prediction in TBI patients, with an 80.78% accuracy rate in recognizing epileptiform anomalies.

Machine learning is used by Thara et al. [73] to forecast the results of paediatric traumatic brain injury (TBI). Support vector machines, neural networks, random forests, logistic regression, naive Bayes, and k-nearest neighbour algorithms are all used in their study, which is carried out in Southern Thailand. Support vector machines show the best results. These ML algorithms show potential as screening tools for prognostic counselling and functional outcome prediction in paediatric traumatic brain injury cases due to their excellent sensitivity and specificity.

EEG-derived psychophysiological indicators were used in a pilot research by Di et al. [74] to predict clinical outcomes in patients with disorders of consciousness (DoC) following brain damage. The translational value of EEG biomarkers in DoC assessment was highlighted by the accurate outcomes predictions for traumatic patients that were obtained by combining dominant frequency measures and functional connectivity, while mutual information combination and functional connectivity best predicted outcomes for nontraumatic patients. In nontraumatic patients, the suggested technique yielded an accuracy of 83.3% (sensitivity = 92.3%, specificity = 60%), and in traumatic patients, an accuracy of 80% (sensitivity = 85.7%, specificity = 71.4%).

Italinna et al. [75] use supervised machine learning and normative modelling to detect mild Traumatic Brain Injury (mTBI) from MEG recordings. The technique improved clinical decision-making by identifying mTBI patients from controls with a 79% accuracy rate.

7. DISCUSSION

The comparative analysis of studies on automatic seizure detection in Table 1 presents a diverse array of methodologies, feature extraction techniques, classification algorithms, and results. Various techniques are studied, including deep learning models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), as well as classic machine learning classifiers and ensemble models. Feature extraction techniques span from simple signal processing techniques like the Discrete Wavelet Transform (DWT) to more complex approaches like Spectral Principal Component Analysis (SpPCA) and Recurrence Plots. Classification algorithms vary widely, including SVMs, LSTM, CatBoost, and novel architectures like attention-gated U-nets. Results showcase high accuracy rates, often surpassing 90%, with some studies achieving perfect classification performance. Sensitivity, specificity, false detection rates, and area under the curve (AUC) are among the reported metrics, demonstrating the robustness and potential clinical utility of the proposed methods in seizure detection. However, further validation and standardization across diverse datasets are necessary to ensure the reliability and generalizability of these automated seizure detection systems.

The comparative analysis of sleep disorder studies in Table 2 reveals a diverse landscape of methodologies, feature extraction techniques, classification algorithms, and results. Deep learning models such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are used in the studies, as well as classic machine learning techniques such as Support Vector Machines (SVMs) and Random Forest. Feature extraction methods span time domain features, frequency domain features, energy in sub-bands, entropy, moments, and multi-level wavelet decomposition, each tailored to capture pertinent information from EEG, ECG, EMG, and PPG signals. Notably, deep learning models emerge as prominent tools, showcasing their prowess in automatically learning intricate patterns from raw data, leading to state-of-the-art performance across various tasks. While traditional methods still find application, the superior performance of deep learning architectures, as evidenced by consistently high accuracy and sensitivity, underscores a paradigm shift in sleep disorder analysis. However, the choice of methodology and feature extraction techniques remains contingent upon the specific objectives and characteristics of the sleep disorder being studied.

The comparative analysis of movement disorder diagnosis studies in Table 3 reveals a diverse range of methodologies, feature extraction techniques, classification algorithms, and achieved results. Researchers use a variety of deep learning architectures, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and their combinations, to evaluate EEG data, ECG signals, and raw MRIs for diagnosis. Machine learning techniques such as Support Vector Machines (SVMs), Logistic Regression (LR), and k-Nearest Neighbours (k-NN) are also used, frequently in combination with sophisticated feature extraction methods such as wavelet transformations and synchronization likelihood features. Results demonstrate high accuracy rates, with some studies achieving almost perfect classification performance, surpassing traditional methods. Additionally, transfer learning and automated feature selection techniques contribute to improved diagnostic accuracy and efficiency. These findings underscore the potential of machine learning and deep learning approaches in enhancing movement disorder diagnosis through the analysis of physiological signals and medical imaging data.

However, further validation on larger and more diverse datasets is essential to ensure the robustness and generalizability of these diagnostic tools in clinical settings.

The comparative analysis of the studies presented in Table 4 reveals a diverse landscape of methodologies, feature extraction techniques, classification algorithms, and results in cognitive assessment using EEG data. While deep learning models dominate the landscape for their ability to extract features directly from raw EEG signals, machine learning techniques also play a significant role, particularly in leveraging more traditional feature extraction methods. Results vary widely across studies, with reported accuracy rates ranging from modest to high levels, influenced by factors such as data quality, feature extraction effectiveness, and algorithm choice. Despite this variability, the studies collectively highlight the potential of EEG-based cognitive assessment in detecting cognitive decline, assessing cognitive workload and differentiating cognitive states, offering promising perspectives for improving clinical diagnosis and human-machine interaction.

Table 1. Comparison of studies on automatic seizure detection

Study	Methodology	Feature Extraction	Classification Algorithm	Result
Ullah et al. [9]	Ensemble of P-1D-CNN models	EEG sub signals	P-1D-CNN	Accuracy of 99.1 ± 0.9% on University of Bonn dataset
Jaiswal et al. [18]	Automated seizure detection	SpPCA, SubXPCA	SVM	100% accuracy for classification of normal and epileptic EEG signals
Hao et al. [19]	Deep learning-based semi-automatic detector	EEG Signals	Deepied (RNN-based)	Median sensitivity of 84.2% with false positive rate set at 5 events/min
Abbasi et al. [14]	Deep learning with LSTM architecture	Hurst Exponent, ARMA	LSTM	Up to 99.17% accuracy for various EEG signal classifications
Aliyu et al. [20]	Recurrent neural network (RNN)	DWT	RNN (with optimizations)	99% accuracy with the best generalization, outperforming other algorithms
Burenter et al. [21]	Spectral analysis of seizure-free EEG recordings	Fine-graded spectral analysis	Ensemble of Classifiers	Accuracy of 99% in diagnosing epilepsy
Amin et al. [22]	Discrete wavelet transform (DWT) and arithmetic coding	DWT	Linear and non-linear machine learning classifiers	Perfect classification performance (100% accuracy) for detecting epileptic seizure activity
Chatzichristos et al. [23]	Attention-gated U-nets and long short-term memory network	Self label EEG	U-net & LSTM	Outperformed state-of -the-art methods, highest TAES score in Neureka 2020 Epilepsy Challenge
Xu et al. [24]	Self-supervised learning method for anomaly detection	Self label EEG	Multi-class classifier using self-labeled normal EEG data	Outperformed classic anomaly detection methods, AUC of 0.943
Mardini et al. [25]	Machine learning classifiers	Self label EEG	ANN	ANN achieved accuracy of 97.82% for detecting epileptic seizures
Malekzadeh et al. [26]	Preprocessing, feature extraction, and classification steps	Tunable-Q Wavelet Transform	CNN–RNN model	Accuracy of 99.5% using 10-fold cross-validation
Thangavel et al. [27]	Deep learning with ConvNets	Various input features, 1D ConvNet model	CNN	False detection rate of 0.23/min at 90% sensitivity, mean EEG classification BAC of 78.1% (AUC of 0.839)

Study	Methodology	Feature Extraction	Classification Algorithm	Result
Zubair et al. [28]	Dimensionality reduction and machine learning	DWT	CatBoost	High accuracy with sensitivity of 98.09%, specificity of 98.69%, and false detection rate of 0.24/h
Shankar et al. [15]	Deep learning with CNN	Recurrence Plots (RP) from EEG signals	CNN	Classification accuracy up to 93% on Bonn University and CHB-MIT databases
Christou et al. [30]	Evaluating impact of different window sizes	EEG signals	BFGS, multistart, modified GA, K-NN	Highest accuracy achieved with 20-21 seconds window size, multistart method reached 81.59% accuracy
Jiwani et al. [29]	Combined CNN and LSTM models	EEG signals	CNN and LSTM	Maximum accuracy of 100% for distinguishing between healthy and seizure patients

Table 2. Comparative analysis of sleep disorder studies

Study	Methodology	Feature Extraction	Classification Algorithm	Result
Chambon et al. [10]	Deep learning with multivariate and multimodal time series	Time domain feature	Deep learning model with linear spatial filters and softmax classifier	State-of-the-art performance with high sensitivity and specificity in detecting sleep stages
Koushik et al. [31]	Deep learning on smartphone, time-distributed 1-D deep convolutional neural network	Time domain feature	1-D deep convolutional neural network	83.5% accuracy for five-class sleep staging
Tzimourta et al. [32]	Filtering EEG signal, calculating energy in sub-bands	Energy in sub-bands	Random Forest, SVM, k-NN, Decision Tree, Na¨ıve Bayes	Best classification accuracy: Random Forest (75.29%)
Korkalainen et al. [33]	Deep learning-based method, single EEG channel, EEG+EOG	Time domain feature	Deep learning architecture	Sleep staging accuracy: 83.7% (single EEG channel), 83.9% (EEG+EOG)
Chambon et al. [34]	Dreem One Shot Event Detector (DOSED), deep learning architecture	Time domain feature	DOSED (deep learning architecture)	Outperforms state-of-the-art methods in event detection
Ravan et al. [35]	Electroencephalography-based machine learning approach, decision tree-based multi-class support vector machine classifier	Quantitative features from EEG signals	Support Vector Machine (SVM)	Average classification accuracy of 94.2% for sleep quality measurement

Study	Methodology	Feature Extraction	Classification Algorithm	Result
Buettner et al. [36]	Machine learning approach for sleep disorder diagnosis using electroencephalographic data	Frequency domain feature	Random Forest	Accuracy of over 90% for classifying REM sleep behaviour disorder
Korkalainen et al. [37]	Deep learning model, PPG data	Time domain feature	Deep learning architecture	Accuracies: 80.1% (3-stage), 68.5% (4-stage), 64.1% (5-stage)
Jarchi et al. [38]	Deep learning, ECG and EMG	Entropy & Moments	Deep Neural Network (DNN)	Accuracy: 72% in recognizing four groups with sleep-related disorders
Sharma et al. [41]	Automated identification of six sleep disorders using EEG signals	Ensemble boosted trees classifier	Ensemble boosted trees classifier	Highest accuracy: 91.3% for identifying the type of sleep disorder
Sudhakar et al. [40]	Detection of sleep disorders using EEG signals and deep learning neural networks	Time domain feature	Convolutional Neural Network (CNN)	Accuracy: 93.33% using AlexNet
Sharma et al. [39]	Automated sleep stage classification using multi-level wavelet decomposition and norm-based feature extraction	Multi-level wavelet decomposition and norm-based feature extraction	Supervised classifiers	Highest accuracy: 92.8% (balanced dataset) for sleep stage classification
Fu et al. [42]	Deep learning model for sleep EEG signals using bidirectional recurrent neural network encoding and decoding	Time & Frequency domain feature	Bidirectional Recurrent Neural Network (BiRNN)	Classification accuracy: 70-85% for each category
Leino et al. [43]	Accurate automatic sleep staging based on ambulatory forehead EEG using deep learning models	Time domain feature	Deep learning architecture	Accuracy: 79.7% (5-stage), 84.1% (4-stage), 89.1% (3-stage) for sleep staging using ambulatory forehead EEG

Table 3. Comparative analysis of movement disorder diagnosis studies

Study	Methodology	Feature Extraction	Classification Algorithm	Result
Vrbancic et al. [11]	Deep Convolutional Neural Networks (CNN)	EEG signals	CNN	Overall accuracy of 69.23%, outperformed traditional methods
Mumtaz et al. [44]	Machine Learning	EEG-derived synchronization likelihood (SL) features	SVM, LR, NB	High accuracy rates achieved for Major Depressive Disorder diagnosis
Vanegas et al. [45]	Machine Learning	EEG-based biomarkers	Extra Tree Classifier (ETC)	Almost perfect classification performance for PD diagnosis
Ruffini et al. [46]	Deep Convolutional Neural Network (DCNN), Deep Recurrent Neural Network (RNN)	EEG data as spectrograms	DCNN, RNN	80% (±1%) classification accuracy in control vs. PD-conversion group
Dai et al. [47]	Convolutional Neural Network (CNN), Variational Autoencoder (VAE)	Combined time, frequency and channel information	CNN-VAE	Outperformed best classification method in literature, improved accuracy by 3%
Koch et al. [48]	Automated Machine Learning	794 features from EEG channels	Automated computed features	Classification accuracy of 84.0%, better performance with automated features alone
Shajil et al. [49]	Transfer Learning	Pre-trained Convolutional Neural Networks (CNNs)	InceptionV3, AlexNet, ResNet50	InceptionV3 achieved highest classification accuracy of 82.78±4.87%
Bouallegue et al. [50]	Dynamic Filtering, Deep Learning	FIR and IIR filters, Gated-Recurrent Unit (GRU), Convolutional Neural Network (CNN)	GRU, CNN	Average accuracy of 100% for epilepsy diagnosis, 99.5% for autism diagnosis
Oh et al. [51]	Convolutional Neural Network (CNN)	EEG signals	CNN	Accuracy: 88.25%, Sensitivity: 84.71%, Specificity: 91.77%
Abdulwahab et al. [52]	Machine Learning	Maximum Overlap Discrete Wavelet Transform (MODWT)	SVM, k-NN, Decision Tree	Average accuracy of 98.81% using MODWT
Bashir et al. [53]	Deep Learning	Raw MRIs	DystoniaNet	Overall accuracy of 98.8% for dystonia diagnosis
Shaban et al. [16]	Deep Learning	Resting state EEG data	Artificial Neural Networks	Accuracy: 98%, Sensitivity: 97%, Specificity: 100%

Study	Methodology	Feature Extraction	Classification Algorithm	Result
Urtnasan et al. [54]	Deep Learning	ECG signals	Deep PLM	F1-score: 92%, Accuracy: 88% in training group
Shahini et al. [55]	Deep Neural Network	Raw EEG data	Deep Neural Network	Accuracy: 96.9% for two-stage, 89.8% for three-stage movement intentions
Shaban et al. [56]	Deep Convolutional Neural Network (CNN)	Wavelet domain of resting-state EEG	CNN	Accuracy: 99.9%, Specificity: 100%, Sensitivity: 97% for classifying HC, PD with and without medication

Table 4. Comparative analysis of cognitive assessment by EEG

Study	Methodology	Feature Extraction	Classification Algorithm	Result
Almogbel et al. [13]	Deep Learning	Raw EEG signals	End-to-end Deep Neural Network model	High accuracy rate of 95.31% for cognitive workload classification without pre-processing or feature engineering
Liu et al. [57]	Machine Learning	EEG recordings	Subject-dependent and Subject-independent fatigue recognition algorithms	Subject-dependent average accuracy of 93.45%, Subject-independent average accuracy of 39.80%
Yang et al. [58]	Deep Learning	EEG signals	Ensemble Classifier based on Subject-specific Integrated Deep Learning Committees	Subject-specific classification accuracy of 92% outperforms classical shallow and deep classifiers
Plechawska et al. [59]	Machine Learning	EEG spectral data	k-Nearest Neighbours (kNN) model	High maximal accuracies achieved, ~91% for validation dataset and cross-validation approach
Almogbel et al. [60]	Deep Learning	Raw EEG signals	End-to-end Deep Neural Network model	Average accuracy of 0.960 for workload and context classification, high recall and precision scores on raw EEG signals
Sridhar et al. [61]	Deep Learning	Brain signal features	Bidirectional Long Short-Term Memory (BLSTM) Network	Outperforms conventional deep neural networks in detecting Mild Cognitive Impairment (MCI)
Qu et al. [62]	Machine Learning	EEG data	Various machine earning and deep learning algorithms	Different tasks (writing vs. typing) can be classified with accuracy up to 70% for individual subjects

Study	Methodology	Feature Extraction	Classification Algorithm	Result
Siuly et al. [63]	Machine Learning	EEG data	Extreme Learning Machine (ELM), Support Vector Machine (SVM), K-Nearest Neighbours (KNN)	ELM-based method achieves the highest classification accuracy of 98.78% for distinguishing MCI from healthy controls
Geraedts et al. [64]	Machine Learning	EEG signals	ML pipeline	High accuracy achieved for differentiating Parkinson's Disease patients based on cognitive function
Gupta et al. [65]	Deep Learning	EEG-based functional connectivity	Mutual Information (MI), Convolutional Neural Network , Phase Locking Value (PLV), Phase Transfer Entropy (PTE)	State-of-the-art accuracy of 80.87% for cognitive workload classification using EEG functional connectivity
Suchetha et al. [66]	Deep Learning	EEG signals	Sequential Convolutional Network (SCN), Multi Branch Convolutional Network (MBCN)	MBCN model outperforms SCN model and traditional methods, achieving high accuracy, F1-score, p recision, and sensitivity
Jiang et al. [17]	Machine Learning	EEG, eye tracking, neuropsychological tests	Machine learning model	Excellent classification performances for screening mild cognitive impairment (MCI) with potential for prediction
Longo et al. [67]	Deep Learning	EEG data	Self-supervised deep learning techniques	Good accuracy and generalizability for mental workload modelling using a brain rate index
Molcho et al. [68]	Machine Learning	EEG features	Machine learning- based EEG features	The proposed tool demonstrates the ability to assess cognitive states and detect cognitive decline

Table 5. Comparative analysis of brain injury assessment by EEG

Study	Methodology	Feature Extraction	Classification Algorithm	Result
Obukhov et al. [12]	EEG-based detection of epileptiform activity	EEG records	Wavelet transform, logistic regression	Accuracy of around 80% in detecting epileptiform activity
Amorim et al. [69]	EEG reactivity for predicting outcomes in hypoxic-ischemic brain injury	EEG reactivity data	Random Forest, GLM, expert review	Comparable performance to expert EEG reactivity assessment for outcome prediction in hypoxic-ischemic brain injury
Vishwanath et al. [70]	Machine learning for identifying biomarkers of TBI	EEG data, CNNs	Convolutional neural networks	Accuracy up to 92.03% in identifying biomarkers of TBI
Wang et al. [71]	Automated detection of Disorders of Consciousness (DoC) in brain-injured patients	EEG signals	Power Spectral Density Difference (PSDD), SVM ensemble	Highest accuracy of 98.21% in detecting DoC and wakefulness in brain-injured patients
Faghihpirayesh et al. [72]	Deep learning for automated detection of epileptiform activity in TBI patients	EEG data	Recurrent neural network	Accuracy of 80.78% in automatically identifying epileptiform abnormalities in TBI patients
Thara et al. [73]	ML prediction of outcomes in paediatric traumatic brain injury (TBI)	Clinical and radiologic characteristics	Support Vector Machines, Neural Networks, Random Forest, Logistic Regression, Naive Bayes, k-NN	High performance in predicting TBI outcomes, with support vector machines achieving the best results
Di et al. [74]	EEG biomarkers for predicting clinical outcome in patients with DoC	EEG biomarkers	Machine learning procedure	Accuracy of 80%-83.3% in predicting clinical outcomes in patients with DoC
Italinna et al. [75]	MEG-based detection of mild traumatic brain injury	MEG recordings	Support Vector Machine	Accuracy of 79% in distinguishing mild TBI patients from controls

The comparative analysis presents in Table 5 presents a comprehensive overview of research endeavors aimed at utilizing EEG and MEG data for assessing brain injuries and predicting clinical outcomes. Each study employs distinct methodologies, ranging from EEG- based detection of epileptiform activity to MEG-based identification of mild traumatic brain injury. Various feature extraction techniques and classification algorithms such as wavelet transform, CNNs, and Support Vector Machines are utilized, reflecting the diversity in analytical approaches. Despite differences in methodologies, the results demonstrate promising accuracies, with some studies achieving accuracies exceeding 90%. These findings underscore the potential of EEG and MEG data as valuable tools in clinical settings for diagnosing brain injuries, monitoring patient outcomes, and guiding treatment decisions. Additionally, the comparative analysis focuses on ongoing advances in machine learning and deep learning approaches, which improve the accuracy and reliability of brain damage assessment methods based on neuroimaging data.

7.1 limitations of the Current Studies

The development of EEG-based diagnostic techniques has the potential to completely transform clinical procedures in a number of areas, such as the diagnosis of movement disorders, the categorization of sleep disorders, the detection of seizures, cognitive evaluation, and the assessment of brain injuries. To guarantee these approaches' effectiveness and applicability in actual healthcare settings, a number of issues and concerns must be taken into account.

- **Seizure Identification using EEG**
  - Difficulty in ensuring model resilience across diverse datasets and real-world situations.
  - Lack of real-time application, limiting immediate therapeutic value.
  - Challenges in model interpretability hinder acceptance by medical professionals.
  - Lack of uniformity in assessment measures and datasets complicates outcome comparison.
  - Computational complexity of deep learning models may hinder deployment in resource-limited settings.
- **Sleep Disorder Classification using EEG**
  - Limited generalizability across different populations and recording settings.
  - Potential oversight of valuable data from other modalities like EOG and EMG.
  - Concerns about interpretability of deep learning models.
  - Absence of standardized assessment measures and datasets complicates comparison.
  - Computational cost of deep learning approaches may limit practical deployment.
- **Movement Disorder Diagnosis using EEG**
  - Difficulty in extrapolating results to larger and more diverse populations.
  - Potential overlook of supplementary information from other modalities.
  - Interpretability concerns with deep learning models.
  - Lack of standardized assessment measures and datasets hampers comparison.
  - Computational complexity of deep learning models may restrict practical deployment.
- **Cognitive Assessment using EEG**
  - Small sample sizes limit generalizability.
  - Inconsistent methodologies across studies hinder replication and comparison.
  - Focus on offline EEG analysis may not capture naturalistic cognitive processes.
  - Interpretability issues with deep learning models.
  - Need for more clinical trials to confirm practicality and therapeutic value.
- **Brain Injury Assessment using EEG**
  - Limited reliability and generalizability due to small sample sizes.
  - Inconsistency in preprocessing methodologies and feature extraction strategies.
  - Interpretability concerns with deep learning and machine learning models.
  - Focus on offline EEG analysis may not capture real-time brain injury progression.
  - Need for standardized procedures and improved model interpretability for practical deployment.

8. CONCLUSION

The comparative analyses conducted amongst various neuroimaging research demonstrate the noteworthy advancements achieved in the application of deep learning and machine learning approaches to neurological diagnoses. This research demonstrates the adaptability and efficacy of sophisticated computational approaches in identifying significant patterns from complicated neuroimaging data, ranging from seizure detection to cognitive evaluation and brain damage prediction. When combined with creative feature extraction techniques and reliable classification algorithms, the impressive performance of deep learning models highlights how automated diagnostic systems have the potential to completely transform clinical practice. However, in order to fully achieve this promise, more work must be done to integrate multimodal neuroimaging data, test and standardize these approaches across a variety of datasets, and resolve issues with regulatory approval and interpretability.

9. FUTURE DIRECTIVES

Future prospects for neuroimaging-based diagnostics research are bright and varied. The development of novel approaches for early detection and personalized treatment planning, the improvement of current diagnostic tools, and the investigation of the synergies between various modalities to obtain a deeper understanding of neurological disorders are all made possible by the advancements in machine learning and deep learning techniques. As technology advances, increasing emphasis is being placed on ethical considerations, ensuring that algorithmic decision-making is transparent and egalitarian, and fostering multidisciplinary collaborations to bridge the knowledge gap between computational neuroscience and clinical practice. Through the utilisation of computational techniques and neuroimaging data, a new age of precision medicine may be ushered in, characterised by patient care that is optimised and personalized due to insights gained from the intricate workings of the human brain.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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